

AN IMPROVED NEGATIVE SELECTION ALGORITHM BASED ON THE  
HYBRIDIZATION OF CUCKOO SEARCH AND DIFFERENTIAL EVOLUTION  
FOR ANOMALY DETECTION

LASISI AYODELE NOJEEEM

A thesis submitted in  
fulfillment of the requirement for the award of the  
Doctor of Philosophy of Information Technology



Faculty of Computer Science and Information Technology  
Universiti Tun Hussein Onn Malaysia

MARCH 2018

In the name of ALLAH,  
The Most Compassionate, The Most Merciful  
All praises and glorifications to ALLAH for the successful completion of my thesis  
Special thanks goes to my beloved father and mother,  
Prof. Dr. Fola Lasisi and Mrs. Olubunmi Lasisi  
For their undiluted love and support  
Gratitude to my brothers and sisters,  
Babatunde, Aminat, Aishat, and Rasheed of the Lasisi Clan  
For their prayers  
To my supervisor,  
Assoc. Prof. Dr. Rozaida Ghazali  
For her indescribable guidance, support, patience, and understanding  
This thesis is dedicated to you all.



PTTAUTHM  
PERPUSTAKAAN TUNKU TUN AMINAH

## ACKNOWLEDGEMENT

I will like to begin by expressing my sincere and utmost gratitude to my supervisor, Assoc. Prof. Dr. Rozaida Ghazali for her acceptance and open arms, constant motivation and support at all times during the course of my study under her guidance. I truly appreciate and value her esteemed guidance and encouragement from the beginning to the end of my study, including the constructive criticisms and comments given in respect to all the facets of this research. I am extremely fortunate and blessed to have a supervisor who cared so much about my well-being, research progress, and who responded to my questions and queries so promptly. I am indebted to her for having helped me shape the problem and providing insights towards the solution.

Also, I am acknowledging the professional advice and assistance of Prof. Dr. Mustafa Mat Deris, Prof. Dr. Rosziati Ibrahim, Prof. Dr. Mohd Nordin Abdul Rahman, Assoc. Prof. Dr. Nazri Mohd Nawawi, Assoc. Prof. Dr. Mohd Najib Mohd Salleh, Assoc. Prof. Dr. Shahreen Kasim, Assoc. Prof. Dr. Hajjah Rathiah Hashim, Assoc. Prof. Dr. Mohd Farhan Md. Fudzee, Dr. Muhaini Othman, and Dr. Nureize Arbaiy in moulding and providing directions on my research. Appreciations to the remaining academic and non-academic staffs of the Faculty of Computer Science and Information Technology, UTHM for their selfless efforts in cooperation with the students. Extending my thanks also to my colleagues, friends, and everyone who contributed directly and indirectly to finalizing this research.

I am showing recognition to the Office for Research, Innovation, Commercialization, and Consultancy Management (ORICC), UTHM and Ministry of Higher Education (MOHE) Malaysia for financially supporting this research under the followings; Geran Insentif Penyelidik Siswazah (GIPS), Vote No. 1160, Fundamental Research Grant Scheme (FRGS), Vote No. 1235, and Exploratory Research Grant Scheme (ERGS), Vote No. 0882.

My deepest appreciation is accorded to my loving father and mother, Prof. Dr. Fola Lasisi and Mrs. Olubunmi Lasisi, as well as my ever supportive brothers and sisters in the persons of Babatunde, Aminat, Aishat, and Rasheed. They have stood by me through thick and thin by supporting with finances and prayers. Alhamdulillah that I am surrounded with the most precious family.

To crown it all, this acknowledgement is without doubt incomplete if honour and praises are not given to Almighty ALLAH for guiding and protecting me through sound health and abundant blessings. I glorify HIS name, Alhamdulillah!.

*Lasisi Ayodele Nojeem, FSKTM, UTHM*

*Parit Raja, Batu Pahat*



PTTA UTHM  
PERPUSTAKAAN TUNKU TUN AMINAH

## ABSTRACT

The biological immune system (BIS) is characterized by networks of cells, tissues, and organs communicating and working in synchronization. It also has the ability to learn, recognize, and remember, thus providing the solid foundation for the development of Artificial Immune System (AIS). Since the emergence of AIS, it has proved itself as an area of computational intelligence. Real-Valued Negative Selection Algorithm with Variable-Sized Detectors (V-Detectors) is an offspring of AIS and demonstrated its potentials in the field of anomaly detection. The V-Detectors algorithm depends greatly on the random detectors generated in monitoring the status of a system. These randomly generated detectors suffer from not been able to adequately cover the non-self space, which diminishes the detection performance of the V-Detectors algorithm. This research therefore proposed CSDE-V-Detectors which entail the use of the hybridization of Cuckoo Search (CS) and Differential Evolution (DE) in optimizing the random detectors of the V-Detectors. The DE is integrated with CS at the population initialization by distributing the population linearly. This linear distribution gives the population a unique, stable, and progressive distribution process. Thus, each individual detector is characteristically different from the other detectors. CSDE capabilities of global search, and use of Lévy flight facilitates the effectiveness of the detector set in the search space. In comparison with V-Detectors, cuckoo search, differential evolution, support vector machine, artificial neural network, naïve bayes, and  $k$ -NN, experimental results demonstrates that CSDE-V-Detectors outperforms other algorithms with an average detection rate of 95.30% on all the datasets. This signifies that CSDE-V-Detectors can efficiently attain highest detection rates and lowest false alarm rates for anomaly detection. Thus, the optimization of the randomly detectors of V-Detectors algorithm with CSDE is proficient and suitable for anomaly detection tasks.

## ABSTRAK

Sistem imun biologi (BIS) mempunyai ciri-ciri rangkaian sel-sel, tisu, dan organ berkomunikasi dan bekerja secara selaras. Ia juga mempunyai keupayaan untuk belajar, mengiktiraf, dan ingat, sekali gus menyediakan asas yang kukuh untuk pembangunan Sistem imun kecerdasan buatan (AIS). Sejak kemunculan AIS, terbukti kebolehgunaannya di dalam bidang kecerdasan komputer. Real-Valued Negative Selection Algorithm with Variable-Sized Detectors (V-Detectors) adalah tergolong didalam bidang AIS dan telah menunjukkan potensinya di dalam bidang pengesanan anomali. Algoritma V-Detectors menjana pelbagai pengesan secara rawak dalam memantau status sistem. Pengesan yang telah dijana secara rawak ini tidak dapat meliputi secukupnya ruang non-self yang mengurangkan prestasi pengesanan algoritma V-Pengesan. Oleh itu, kajian ini telah mencadangkan CSDE-V-Detectors yang melibatkan penggunaan penghibridan Cuckoo Search (CS) dan Differential Evolution (DE) dalam mengoptimumkan pengesanan rawak bagi V-Pengesan. DE telah disepadukan dengan CS pada populasi pengawalan dengan mengagihkan populasi secara linear. Pengedaran linear ini memberikan satu proses pengedaran unik, stabil dan progresif kepada populasi tersebut. Oleh itu, setiap pengesan adalah bersifat berbeza daripada pengesan yang lain. Keupayaan CSDE dalam carian global dan penggunaan Lévy flight memudahkan keberkesanan set pengesan dalam ruang carian. Di dalam perbandingan dengan V-Pengesan, cuckoo search, differential evolution, mesin vector sokongan, rangkaian neural buatan, bayes naïf, dan  $k$ -NN, keputusan eksperimen pada set data tertentu yang dipilih daripada pangkalan data yang berbeza menunjukkan bahawa CSDE-V-Detectors melebihi performa algoritma lain secara purata dengan kadar 95.30%. Ini menunjukkan CSDE-V-Detectors lebih efisien sehingga boleh mencapai kadar pengesanan yang tinggi dan kadar penggera palsu yang paling rendah pada pengesanan anomali. Oleh itu, pengoptimuman secara pengesana rawak bagi algoritma V-Pengesan dengan CSDE adalah cekap dan sesuai bagi melaksanakan tugas-tugas pengesanan anomali.

## CONTENTS

<b>DECLARATION</b>	<b>ii</b>
<b>DEDICATION</b>	<b>iii</b>
<b>ACKNOWLEDGEMENT</b>	<b>iv</b>
<b>ABSTRACT</b>	<b>vi</b>
<b>ABSTRAK</b>	<b>vii</b>
<b>CONTENTS</b>	<b>viii</b>
<b>LIST OF TABLES</b>	<b>xiii</b>
<b>LIST OF FIGURES</b>	<b>xv</b>
<b>LIST OF ALGORITHMS</b>	<b>xviii</b>
<b>LIST OF SYMBOLS AND ABBREVIATIONS</b>	<b>xix</b>
<b>LIST OF PUBLICATIONS</b>	<b>xxi</b>
<b>CHAPTER 1 INTRODUCTION</b>	<b>1</b>
1.1    Background of the Research	1
1.2    Problem Statement	3
1.3    Aims and Objectives	5
1.4    Scope of the Research	6
1.5    Significance of the Research	7
1.6    Thesis Organization	8
<b>CHAPTER 2 LITERATURE REVIEW</b>	<b>10</b>
2.1    Introduction	10
2.2    Anomaly Detection	10
2.2.1    Anomaly detection problem definition	13
2.3    Biological Immune System	14
2.3.1    Immune System Cells	15

	2.3.1.1	Lymphocytes	16
	2.3.1.2	Phagocytes	16
	2.3.1.3	Dendritic Cells	16
2.3.2		Anatomy of the Immune System	17
	2.3.2.1	Bone Marrow	17
	2.3.2.2	Lymph Nodes	17
	2.3.2.3	Spleen	18
	2.3.2.4	Thymus	19
2.3.3		The Immunological Response	19
	2.3.3.1	Antibody responses	20
	2.3.3.2	Cell-mediated immune responses	20
2.4		Artificial Immune System	21
	2.4.1	Clonal Selection Algorithm	24
	2.4.2	Artificial Immune Network Algorithm	25
	2.4.3	Danger Theory Inspired Algorithms	25
	2.4.4	Dendritic Cell Algorithm	26
2.5		Negative Selection Algorithm	27
	2.5.1	String-based Negative Selection Algorithm	28
	2.5.2	Real-Valued Negative Selection Algorithm	30
	2.5.3	Real-Valued Negative Selection Algorithm with Variable-Sized Detectors (V-Detectors)	31
	2.5.4	Allocating Parameters for V-Detectors Algorithm	35
	2.5.5	Data Representation and Matching Techniques	36
	2.5.5.1	Matching Rule for Strings Representation	37
	2.5.5.2	Matching Rule for Real-Valued Representation	39
	2.5.6	Gap Analysis of current/existing approaches for Negative Selection Algorithm	40
2.6		Optimization Algorithm	45
	2.6.1	Cuckoo Search	46
	2.6.1.1	Lévy Flights	48



2.6.1.2	Algorithm Process of Cuckoo Search	48
2.6.1.3	Advantages of Cuckoo Search	53
2.6.1.4	Allocating Parameters for Cuckoo Search	54
2.6.2	Differential Evolution	54
2.6.2.1	Algorithm Process of Differential Evolution	55
2.7	Overview of Support Vector Machine, Artificial Neural Network, $k$ -Nearest Neighbor, and Naïve Bayes	60
2.7.1	Support Vector Machine (SVM)	60
2.7.2	Artificial Neural Network (ANN)	62
2.7.3	$k$ -Nearest Neighbor ( $k$ -NN)	63
2.7.4	Naïve Bayes (NB)	64
2.8	Discussion: Scenario Leading to the Research Framework	65
2.9	Chapter Summary	68
<b>CHAPTER 3 RESEARCH METHODOLOGY</b>		<b>69</b>
3.1	Introduction	69
3.2	Research Framework	69
3.2.1	Stage One: Data Preparation	71
3.2.1.1	Data Collection	71
3.2.1.2	Data Preprocessing	77
3.2.1.3	Data Partitioning	81
3.2.2	Stage Two: Detector generation of Real-valued negative selection algorithm with Variable-sized Detectors (V-Detectors)	81
3.2.2.1	V-Detectors Structure	82
3.2.2.2	Matching Rule	82
3.2.2.3	Nature-Inspired Metaheuristic Optimization Algorithm	83
3.2.3	Stage Three: Analysis of Results	85
3.2.3.1	Detection Rate	86
3.2.3.2	False Alarm Rate	86
3.2.3.3	Specificity	86
3.2.3.4	Positive Predictive Value	87
3.2.3.5	F-measure	87



3.2.3.6	Matthews Correlation Coefficient	87
3.3	Statistical Analysis Performance Evaluation	88
3.3.1	The Friedman Test	88
3.3.2	Post hoc test	89
3.4	Environment	89
3.5	Parameter Settings for the Proposed Algorithms	89
3.5.1	Hybrid Cuckoo Search and Differential Evolution	90
3.5.2	Optimized V-Detectors with CSDE algorithm	91
3.6	Chapter Summary	92

## **CHAPTER 4 CUCKOO SEARCH-DIFFERENTIAL EVOLUTION FOR V-DETECTORS ALGORITHM OPTIMIZATION 93**

4.1	Introduction	93
4.2	Metaheuristic algorithm for V-Detectors Optimization	94
4.3	Cuckoo Search-Differential Evolution (CSDE) Algorithm	94
4.4	Cuckoo Search-Differential Evolution Optimization of V-Detectors Algorithm (CSDE-V-Detectors)	100
4.5	Computation of the fitness function	104
4.6	Insightful Comparison of V-Detectors and Proposed CSDE-V-Detectors	108
4.7	Chapter Summary	109

## **CHAPTER 5 SIMULATION RESULTS AND DISCUSSION 110**

5.1	Chapter Introduction	110
5.2	Experimental Procedure	110
5.3	Matching Rule	111
5.4	Results of the V-Detectors and CSDE-V-Detectors	111
5.5	Justification for the False Alarm Rates of CSDE-V-Detectors and V-Detectors	118
5.6	Detection performance results of the proposed CSDE-V-Detectors in comparison with standard algorithms	118
5.7	Performance of the Proposed CSDE-V-Detectors	125

5.8	Receiver Operating Characteristic	150
5.9	Area Under the ROC Curve	156
5.10	Statistical Analysis Performance Evaluation	159
5.10.1	The Friedman Test	159
5.10.2	Post hoc test	161
5.11	Discussion on the characteristics of datasets towards CSDE-V-Detectors performance	162
5.12	Chapter Summary	164

## **CHAPTER 6 CONCLUSION AND FUTURE WORK** **165**

6.1	Introduction	165
6.2	Research Summary	165
6.3	Research Contribution	168
6.4	Future Works	169
6.5	Concluding Remarks	170

## **REFERENCES** **171**

## **VITA** **199**



## LIST OF TABLES

2.1	Parameter settings for V-Detectors algorithm	36
2.2	Parameter settings for Cuckoo Search algorithm	54
3.1	Characteristics of the Datasets	77
3.2	Confusion matrix with four performance indicators	86
3.3	Parameter settings for Hybrid CSDE algorithm	90
3.4	Parameter settings for CSDE-V-Detectors algorithm	91
4.1	Comparison between V-Detectors and CSDE-V-Detectors	108
5.1	Simulation results for Iris Dataset	112
5.2	Simulation results for Breast Cancer Dataset	112
5.3	Simulation results for Liver Disorders Dataset	113
5.4	Simulation results for Lenses Dataset	113
5.5	Simulation results for Diabetes Dataset	114
5.6	Simulation results for Balance-Scale Dataset	114
5.7	Simulation results for MONK-2 Dataset	115
5.8	Simulation results for Skin Segmentation Dataset	115
5.9	Simulation results for Banknote Authentication Dataset	116
5.10	Simulation results for Biomed Dataset	116
5.11	Simulation results for Brent Crude Oil Dataset	117
5.12	Simulation results for OPEC Carbon Dioxide Emission Dataset	117
5.13	Iris Dataset Results	119
5.14	Breast Cancer Dataset Results	119
5.15	Liver Disorders Dataset Results	119
5.16	Lenses Dataset Results	120
5.17	Diabetes Dataset Results	121
5.18	Balance-Scale Dataset Results	121
5.19	MONK-2 Dataset Results	121
5.20	Skin Segmentation Dataset Results	122
5.21	Banknote Authentication Dataset Results	123
5.22	Biomed Dataset Results	123
5.23	Brent Crude Oil Dataset Results	123
5.24	OPEC Carbon Dioxide Emission Dataset Results	124

5.25	Performance Outcome for Iris Dataset	126
5.26	Performance Outcome for Breast Cancer Dataset	126
5.27	Performance Outcome for Liver Disorders Dataset	126
5.28	Performance Outcome for Lenses Dataset	127
5.29	Performance Outcome for Diabetes Dataset	134
5.30	Performance Outcome for Balance-Scale Dataset	134
5.31	Performance Outcome for MONK-2 Dataset	134
5.32	Performance Outcome for Skin Segmentation Dataset	135
5.33	Performance Outcome for Banknote Authentication Dataset	142
5.34	Performance Outcome for Biomed Dataset	142
5.35	Performance Outcome for Brent Crude Oil Dataset	142
5.36	Performance Outcome for OPEC Carbon Dioxide Emission Dataset	143
5.37	AUC for Iris and Breast Cancer Datasets	156
5.38	AUC for Liver Disorders and Lenses Datasets	156
5.39	AUC for Diabetes and Balance-Scale Datasets	157
5.40	AUC for MONK-2 and Skin Segmentation Datasets	157
5.41	AUC for Banknote Authentication and Biomed Datasets	157
5.42	AUC for Brent Crude Oil and OPEC Carbon Dioxide Emission Datasets	158
5.43	The Detection Rate for all the algorithms on different dataset problems	160
5.44	The final average rank $R_j$ for all algorithms	160
5.45	Holm's Post hoc test for pairwise comparison at $\alpha = 0.05$	162
5.46	Detection Rate for CSDE-V-Detectors on dataset problems	163

## LIST OF FIGURES

2.1	Point anomalies in a two-dimensional data	12
2.2	Contextual anomaly in a time series data	12
2.3	Collective anomaly in a human electrocardiogram output	13
2.4	Anatomy of the Immune System	18
2.5	The antigen antibody binding	21
2.6	Generation Stage of Negative Selection Algorithm	29
2.7	Detection Stage of Negative Selection Algorithm	29
2.8	Flowchart of Detector Generation for V-Detectors Algorithm	34
2.9	Flowchart of Cuckoo Search	52
2.10	Flowchart of Differential Evolution	59
2.11	SVM mapping through kernel	61
2.12	Architecture of Artificial Neural Network	63
2.13	Scenario Leading to the Research Framework	67
3.1	The Research Framework	70
4.1	The evolution of proposed CSDE Optimization of V-Detectors	94
4.2	Flowchart of Cuckoo Search-Differential Evolution	96
4.3	Flowchart of CSDE detector generation algorithm of the V-Detectors	107
5.1	Graph Plots for SVM (1), ANN (2), and Naïve Bayes (3) (Iris)	128
5.2	Graph Plots for $k$ -NN (4), CS (5), and DE (6) (Iris)	128
5.3	Graph Plots for V-Detectors (7) and CSDE-V-Detectors (8) (Iris)	129
5.4	Graph Plots for SVM (1), ANN (2), and Naïve Bayes (3) (Breast Cancer)	129
5.5	Graph Plots for $k$ -NN (4), CS (5), and DE (6) (Breast Cancer)	130
5.6	Graph Plots for V-Detectors (7) and CSDE-V-Detectors (8) (Breast Cancer)	130
5.7	Graph Plots for SVM (1), ANN (2), and Naïve Bayes (3) (Liver Disorders)	131
5.8	Graph Plots for $k$ -NN (4), CS (5), and DE (6) (Liver Disorders)	131

5.9	Graph Plots for V-Detectors (7) and CSDE-V-Detectors (8) (Liver Disorders)	132
5.10	Graph Plots for SVM (1), ANN (2), and Naïve Bayes (3) (Lenses)	132
5.11	Graph Plots for $k$ -NN (4), CS (5), and DE (6) (Lenses)	133
5.12	Graph Plots for V-Detectors (7) and CSDE-V-Detectors (8) (Lenses)	133
5.13	Graph Plots for SVM (1), ANN (2), and Naïve Bayes (3) (Diabetes)	136
5.14	Graph Plots for $k$ -NN (4), CS (5), and DE (6) (Diabetes)	136
5.15	Graph Plots for V-Detectors (7) and CSDE-V-Detectors (8) (Diabetes)	137
5.16	Graph Plots for SVM (1), ANN (2), and Naïve Bayes (3) (Balance-Scale)	137
5.17	Graph Plots for $k$ -NN (4), CS (5), and DE (6) (Balance-Scale)	138
5.18	Graph Plots for V-Detectors (7) and CSDE-V-Detectors (8) (Balance-Scale)	138
5.19	Graph Plots for SVM (1), ANN (2), and Naïve Bayes (3) (MONK-2)	139
5.20	Graph Plots for $k$ -NN (4), CS (5), and DE (6) (MONK-2)	139
5.21	Graph Plots for V-Detectors (7) and CSDE-V-Detectors (8) (MONK-2)	140
5.22	Graph Plots for SVM (1), ANN (2), and Naïve Bayes (3) (Skin Segmentation)	140
5.23	Graph Plots for $k$ -NN (4), CS (5), and DE (6) (Skin Segmentation)	141
5.24	Graph Plots for V-Detectors (7) and CSDE-V-Detectors (8) (Skin Segmentation)	141
5.25	Graph Plots for SVM (1), ANN (2), and Naïve Bayes (3) (Banknote Authentication)	144
5.26	Graph Plots for $k$ -NN (4), CS (5), and DE (6) (Banknote Authentication)	145
5.27	Graph Plots for V-Detectors (7) and CSDE-V-Detectors (8) (Banknote Authentication)	145
5.28	Graph Plots for SVM (1), ANN (2), and Naïve Bayes (3) (Biomed)	146
5.29	Graph Plots for $k$ -NN (4), CS (5), and DE (6) (Biomed)	146
5.30	Graph Plots for V-Detectors (7) and CSDE-V-Detectors (8) (Biomed)	147

5.31	Graph Plots for SVM (1), ANN (2), and Naïve Bayes (3) (Brent Crude Oil)	147
5.32	Graph Plots for $k$ -NN (4), CS (5), and DE (6) (Brent Crude Oil)	148
5.33	Graph Plots for V-Detectors (7) and CSDE-V-Detectors (8) (Brent Crude Oil)	148
5.34	Graph Plots for SVM (1), ANN (2), and Naïve Bayes (3) (OPEC Carbon Dioxide Emission)	149
5.35	Graph Plots for $k$ -NN (4), CS (5), and DE (6) (OPEC Carbon Dioxide Emission)	149
5.36	Graph Plots for V-Detectors (7) and CSDE-V-Detectors (8) (OPEC Carbon Dioxide Emission)	150
5.37	ROC curve for Iris Dataset	151
5.38	ROC curve for Breast Cancer Dataset	151
5.39	ROC curve for Liver Disorders Dataset	151
5.40	ROC curve for Lenses Dataset	152
5.41	ROC curve for Diabetes Dataset	152
5.42	ROC curve for Balance-Scale Dataset	152
5.43	ROC curve for MONK-2 Dataset	153
5.44	ROC curve for Skin Segmentation Dataset	153
5.45	ROC curve for Banknote Authentication Dataset	153
5.46	ROC curve for Biomed Dataset	154
5.47	ROC curve for Brent Crude Oil Dataset	154
5.48	ROC curve for OPEC Carbon Dioxide Emission Dataset	154





## LIST OF ALGORITHMS

ALGO. NO.	TITLE	PAGE
1	Detector generation of the V-Detectors Algorithm	33
2	Cuckoo Search Algorithm via Lévy flight	53
3	Pseudocode for Differential Evolution Algorithm	58
4	Detector generation algorithm based on nature-inspired metaheuristic	84
5	Hybrid Cuckoo Search-Differential Evolution Algorithm	100
6	CSDE detector generation algorithm of the V-Detectors	106



PTTAUTHM  
PERPUSTAKAAN TUNKU TUN AMINAH

## LIST OF SYMBOLS AND ABBREVIATIONS

$\subset$	–	Proper subset
$\subseteq$	–	Subset
$\in$	–	Element of
$U$	–	Universe
$\mathbb{R}$	–	Real number set
$\cap$	–	Intersection
$\emptyset$	–	Empty set
$N_c$	–	Total number of clones
$N$	–	Size of the antibody pool
$ab$	–	Antibody
$ag$	–	Antigen
$L$	–	Length of bit string
$r_s$	–	Self radius
$r_d$	–	Detector radius
$T_{max}$	–	Maximum number of detector
$m_{max}$	–	The counter limit
$c_0$	–	Estimated coverage
$D(X_i, c_d)$	–	Euclidean distance between self sample $X_i$ and detector $d$ based on detector centre $c_d$
$X$	–	Set of self samples
$\forall$	–	For all or for any
$\exists$	–	There exists
$p_a$	–	Probability of host discovering a cuckoo's egg
$\Gamma$	–	Gamma distribution
$CO_2$	–	Carbon dioxide
$MaxGen$	–	Maximum number of generation
$D$	–	Set of detectors
AIS	–	Artificial Immune System
BIS	–	Biological Immune System
NSA	–	Negative Selection Algorithm
V-Detectors	–	Real-Valued Negative Selection Algorithm with Variable-Sized Detectors
CS	–	Cuckoo Search
DE	–	Differential Evolution
CLONALG	–	CLONal selection ALGORITHM
AINE	–	Artificial Immune NETWORKS
DCA	–	Dendritic Cell Algorithm

RNSA	–	Real-Valued Negative Selection Algorithm with Constant-Sized Detectors
TP	–	True Positive
FN	–	False Negative
FP	–	False Positive
TN	–	True Negative
DR	–	Detection Rate
FAR	–	False Alarm Rate
SP	–	Specificity
PPV	–	Positive Predictive Value
MCC	–	Matthews Correlation Coefficient
SVM	–	Support Vector Machine
ANN	–	Artificial Neural Network
<i>k</i> -NN	–	<i>k</i> -Nearest Neighbor
NB	–	Naïve Bayes
MATLAB	–	MATrix LABoratory
APC	–	Antigen Presenting Cell
MHC	–	Major Histocompatibility Complex
NAT	–	Network Affinity Threshold
ARB	–	Artificial Recognition Ball
SNS	–	Self-Non_Self
PSO	–	Particle Swarm Optimization
GA	–	Genetic Algorithm
<i>exp</i>	–	exponential
<i>bin</i>	–	binomial
OSH	–	Optimal Separating Hyperplane
QP	–	Quadratic Programming
EIA	–	Energy Information Administration
OPEC	–	Organization of the Petroleum Exporting Countries
PC	–	Personal Computer
CPU	–	Central Processing Unit
RAM	–	Random Access Memory
ROC	–	Receiver Operating Characteristic
AUC	–	Area Under the ROC Curve

## LIST OF PUBLICATIONS

### Journals:

- (i) Ayodele Lasisi, Rozaida Ghazali, Mustafa Mat Deris, Tutut Herawan, and Fola Lasisi, "Extracting Information in Agricultural Data Using Fuzzy-Rough Sets Hybridization and Clonal Selection Theory Inspired Algorithms," *International Journal of Pattern Recognition and Artificial Intelligence*, Vol. 30, No. 09, pp. 1660008, 2016.

### Book Chapters:

- (i) Ayodele Lasisi, Rozaida Ghazali, and Tutut Herawan, "Application of Real-Valued Negative Selection Algorithm to Improve Medical Diagnosis," in *Applied Computing in Medicine and Health*, Dhiya Al-Jumeily, Abir Hussain, Conor Mallucci, Carol Oliver, Eds. Waltham, MA: Morgan Kaufmann, 2015, pp. 231-243.
- (ii) Ayodele Lasisi, and Rozaida Ghazali, "Predicting Crude Oil Price Using Fuzzy Rough Set and Real-Valued Negative Selection Algorithm," in *Computational Intelligence and Nature-Inspired Algorithms in Energy*. Springer, 2017. (Accepted for Publication)

### Conference Proceedings:

- (i) Lasisi Ayodele Nojeem, and Rozaida Ghazali, "The Impact of Artificial Immune System for Anomaly Detection," in *Proceedings of International Conference on Science, Technology, Education, Arts, Management & the Social Sciences (iSTEAMS) Research Nexus Conference*, University of Ibadan, Ibadan Nigeria, 2013.
- (ii) Ayodele Lasisi, Rozaida Ghazali, and Tutut Herawan, "Negative Selection Algorithm: A Survey on the Epistemology of Generating Detectors," in *Proceedings of the First International Conference on Advance Data and Information Engineering (DaEng-2013)*. Springer, 2014, pp. 167-176.
- (iii) Ayodele Lasisi, Rozaida Ghazali, and Tutut Herawan, "Comparative Performance Analysis of Negative Selection Algorithm with Immune and Classification Algorithms," in *Recent Advances on Soft Computing and Data Mining*. Springer, 2014, pp. 441-452.
- (iv) Siti Zulaikha Abu Bakar, Rozaida Ghazali, Lokman Hakim Ismail, Tutut Herawan, and Ayodele Lasisi, "Implementation of Modified Cuckoo Search Algorithm on Functional Link Neural Network for Climate Change Prediction via Temperature and Ozone Data," in *Recent Advances on Soft Computing and Data Mining*. Springer, 2014, pp. 239-247.
- (v) Ayodele Lasisi, Rozaida Ghazali, Tutut Herawan, and Haruna Chiroma, "Orchestrating Real-Valued Negative Selection Algorithm with Computational Efficiency for Crude Oil Price," in *International Conference on Intelligent Computing*. Springer, 2015, pp. 387-396.
- (vi) Ayodele Lasisi, Rozaida Ghazali, Tutut Herawan, Fola Lasisi, and Mustafa Mat Deris, "Knowledge Extraction of Agricultural Data Using Artificial Immune System," in *Fuzzy Systems and Knowledge Discovery (FSKD), 2015 12<sup>th</sup> International Conference on*. IEEE, 2015, pp. 1653-1658.
- (vii) Rihab Salah Khairy, Rozaida Ghazali, and Ayodele Lasisi, "Real-Valued Negative Selection Algorithms: Ensuring Data Integrity Through Anomaly Detection," in *Advanced Computer and Communication Engineering Technology*. Springer, 2016, pp. 23-32.

- (viii) Ayodele Lasisi, Rozaida Ghazali, and Haruna Chiroma, "Utilizing Clonal Selection Theory Inspired Algorithms and K-Means Clustering for Predicting OPEC Carbon Dioxide Emissions from Petroleum Consumption," in *International Conference on Soft Computing and Data Mining*. Springer, 2016, pp. 101-110.



PTTA UTHM  
PERPUSTAKAAN TUNKU TUN AMINAH

## CHAPTER 1

### INTRODUCTION

#### 1.1 Background of the Research

The birth of Artificial Immune System (AIS) has brought a new lease of life in discovering changes in data and system as a whole. The inspiration from Biological Immune System (BIS), which is a unique, robust and orchestrated system against the influx of pathogens, viruses, and bacteria, makes AIS a force to be reckoned with. It could prove a vital point in overcoming the various security and detection problems in existence because the exact purpose of the Immune system still remains hidden to researchers and computer scientists. Varieties of detection techniques have evolved over the years and they have produced amazing results for both known and unknown discoveries. As improvements are made for efficiency, the *not – yet – seen* lethal elements always have a way of bypassing the defense systems of the algorithms due to inbuilt obfuscation methods. Anomaly detection, a one-class classification problem, where a single class of object is described and distinguished from all other types of objects [1], encompasses the overall functions of the AIS. Task of anomaly detection is to classify an element as *normal* or *abnormal* within a given feature space [2], and their targeted aim is to detect abnormal behaviours of system that contradicts to the normal functioning of the system [3,4]. Negative Selection Algorithm (NSA) [5], which is well rooted in distinguishing between self and non-self, is an AIS model for tackling anomaly detection problems in an attempt to speed up detection accuracy of novel attack patterns.

The real-valued negative selection algorithm with variable-sized detectors (V-Detectors) [6] is employed for use in this research. It models the biological functionalities of the  $T$ -cells in protecting the body by censoring and eliminating alien invaders called pathogens. The development process emanates from the thymus and differentiates into matured  $T$ -cells without mapping and reacting to self antigens. They are now granted passage into the body circulatory system to fulfil its purpose for existence, which is detecting non-self antigens and adequately causing their annihilation. At the core of the algorithm is the matching rule that matches the antibodies to the antigens, and also the self radius which is a determinant in producing detectors. The efficiency of the V-Detectors is affected by the random process of generating detectors. As such, more productive ways of producing robust and competent detectors are devised by researchers. One of such channels lies with metaheuristic algorithms which are natural optimization techniques. Through mutation, crossover, and selection, global optimality can be achieved. Therefore, a hybridized optimization algorithm based on Cuckoo Search (CS) [7] and Differential Evolution (DE) [8] is proposed as an alternative detector generator for the V-Detectors. This infusion of both metaheuristic algorithms makes use of Lévy flight for its search ability, thereby enabling global search convergence [9].

Increased performance of the V-Detectors can thus be obtained with the hybridized optimization algorithm of CS and DE. The proposed anomaly detection method can assist in effectively checking a system in order to maintain its normal functionality and triggering suspicion of any abnormality that could arise.



## REFERENCES

1. T. Stibor, J. Timmis, and C. Eckert, "The link between r-contiguous detectors and k-cnf satisfiability," in *Evolutionary Computation, 2006. CEC 2006. IEEE Congress on.* IEEE, 2006, pp. 491–498.
2. R. Kaur and S. Singh, "A survey of data mining and social network analysis based anomaly detection techniques," *Egyptian Informatics Journal*, vol. 17, no. 2, pp. 199–216, 2016.
3. B. Liu, Y. Xiao, S. Y. Philip, Z. Hao, and L. Cao, "An efficient approach for outlier detection with imperfect data labels," *IEEE Transactions on Knowledge and Data Engineering*, vol. 26, no. 7, pp. 1602–1616, 2014.
4. U. Aickelin, D. Dasgupta, and F. Gu, "Artificial immune systems," in *Search Methodologies.* Springer, 2014, pp. 187–211.
5. S. Forrest, A. S. Perelson, L. Allen, and R. Cherukuri, "Self-nonself discrimination in a computer," in *Research in Security and Privacy, 1994. Proceedings., 1994 IEEE Computer Society Symposium on.* IEEE, 1994, pp. 202–212.
6. Z. Ji and D. Dasgupta, "Real-valued negative selection algorithm with variable-sized detectors," in *Genetic and Evolutionary Computation—GECCO 2004.* Springer, 2004, pp. 287–298.
7. X.-S. Yang and S. Deb, "Cuckoo search via lévy flights," in *Nature & Biologically Inspired Computing, 2009. NaBIC 2009. World Congress on.* IEEE, 2009, pp. 210–214.
8. R. Storn and K. Price, *Differential evolution—a simple and efficient adaptive scheme for global optimization over continuous spaces.* ICSI Berkeley,

- 1995, vol. 3.
9. X.-S. Yang and S. Deb, "Multiobjective cuckoo search for design optimization," *Computers & Operations Research*, vol. 40, no. 6, pp. 1616–1624, 2013.
  10. D. Dasgupta, S. Yu, and F. Nino, "Recent advances in artificial immune systems: models and applications," *Applied Soft Computing*, vol. 11, no. 2, pp. 1574–1587, 2011.
  11. Z. Lu, G. Pei, B. Liu, and Z. Liu, "Hardware implementation of negative selection algorithm for malware detection," in *Electron Devices and Solid-State Circuits (EDSSC), 2015 IEEE International Conference on*. IEEE, 2015, pp. 301–304.
  12. P. Saurabh and B. Verma, "A cooperative negative selection algorithm for anomaly detection," *International Journal of Computer Applications*, vol. 95, no. 17, 2014.
  13. D. Dasgupta, S. Yu, and N. S. Majumdar, "Milamultilevel immune learning algorithm," in *Genetic and Evolutionary Computation Conference*. Springer, 2003, pp. 183–194.
  14. F. Gonzalez, D. Dasgupta, and R. Kozma, "Combining negative selection and classification techniques for anomaly detection," in *Evolutionary Computation, 2002. CEC'02. Proceedings of the 2002 Congress on*, vol. 1. IEEE, 2002, pp. 705–710.
  15. S. L. Rosa, S. M. Shamsuddin *et al.*, "An immune based patient anomaly detection using rfid technology," *Computer Engineering and Applications Journal*, vol. 2, no. 1, p. 121, 2013.
  16. T. F. Ghanem, W. S. Elkilani, and H. M. Abdul-Kader, "A hybrid approach for efficient anomaly detection using metaheuristic methods," *Journal of advanced research*, vol. 6, no. 4, pp. 609–619, 2015.
  17. D. Li, S. Liu, and H. Zhang, "A boundary-fixed negative selection algorithm with online adaptive learning under small samples for anomaly detection,"

- Engineering Applications of Artificial Intelligence*, vol. 50, pp. 93–105, 2016.
18. C. Wen, D. Xiaoming, L. Tao, and Y. Tao, “Negative selection algorithm based on grid file of the feature space,” *Knowledge-Based Systems*, vol. 56, pp. 26–35, 2014.
  19. I. Aydin, M. Karakose, and E. Akin, “Chaotic-based hybrid negative selection algorithm and its applications in fault and anomaly detection,” *Expert Systems with Applications*, vol. 37, no. 7, pp. 5285–5294, 2010.
  20. M. Majd, A. Hamzeh, and S. Hashemi, “A polymorphic convex hull scheme for negative selection algorithms,” *International Journal of Innovative Computing, Information and Control*, vol. 8, no. 5A, pp. 2953–2964, 2012.
  21. R. H. Hu, P. H. Lou, and P. Zhao, “A novel approach of detector generation for real-valued negative selection algorithm,” *Applied Mechanics and Materials*, vol. 121, pp. 3736–3740, 2012.
  22. J. M. Shapiro, G. B. Lamont, and G. L. Peterson, “An evolutionary algorithm to generate hyper-ellipsoid detectors for negative selection,” in *Proceedings of the 2005 conference on Genetic and evolutionary computation*. ACM, 2005, pp. 337–344.
  23. G. Li, T. Li, J. Zeng, and H. Li, “An outlier robust negative selection algorithm inspired by immune suppression,” *Journal of Computers*, vol. 5, no. 9, pp. 1348–1355, 2010.
  24. T. Pourhabibi and R. Azmi, “Anomaly based ids using variable size detector generation in ais: a hybrid approach,” *International Journal of Information System Security*, vol. 1, no. 1, pp. 1–14, 2011.
  25. X. Gao, S. Ovaska, and X. Wang, “Genetic algorithms-based detector generation in negative selection algorithm,” in *Adaptive and Learning Systems, 2006 IEEE Mountain Workshop on*. IEEE, 2006, pp. 133–137.
  26. W. Ma, D. Tran, and D. Sharma, “Negative selection with antigen feedback in intrusion detection,” in *Artificial Immune Systems*. Springer, 2008, pp. 200–209.

27. I. Idris, A. Selamat, N. T. Nguyen, S. Omatu, O. Krejcar, K. Kuca, and M. Penhaker, "A combined negative selection algorithm–particle swarm optimization for an email spam detection system," *Engineering Applications of Artificial Intelligence*, vol. 39, pp. 33–44, 2015.
28. P. Saurabh and B. Verma, "An efficient proactive artificial immune system based anomaly detection and prevention system," *Expert Systems with Applications*, vol. 60, pp. 311–320, 2016.
29. Z. Liu, T. Li, J. Yang, and T. Yang, "An improved negative selection algorithm based on subspace density seeking," *IEEE Access*, vol. 5, pp. 12 189–12 198, 2017.
30. X. Zheng, Y. Zhou, and Y. Fang, "The dual negative selection algorithm and its application for network anomaly detection," *International Journal of Information and Communication Technology*, vol. 11, no. 1, pp. 94–118, 2017.
31. C. Blake and C. J. Merz, "UCI repository of machine learning databases," *University of California, Irvine, Department of Information and Computer Sciences*, 2002.
32. P. Vlachos, "Statlib datasets archive," URL <http://lib.stat.cmu.edu/datasets>, 2005.
33. "United states energy information administration (eia)," June 23 2015. [Online]. Available: <http://www.eia.doe.gov/>
34. "Energy information administration of the united states department of energy," May 27 2014. [Online]. Available: <http://www.eia.gov/cfapps/ipdbproject/iedindex3.cfm?tid=5&pid=5&aid=8&cid=CG9,&syid=1980&eyid=2011&unit=MMTCD>
35. V. Chandola, A. Banerjee, and V. Kumar, "Anomaly detection: A survey," *ACM Computing Surveys (CSUR)*, vol. 41, no. 3, p. 15, 2009.
36. M. Goldstein and S. Uchida, "A comparative evaluation of unsupervised anomaly detection algorithms for multivariate data," *PloS one*, vol. 11, no. 4,

- p. e0152173, 2016.
37. S. R. Arashloo, J. Kittler, and W. Christmas, "An anomaly detection approach to face spoofing detection: A new formulation and evaluation protocol," *IEEE Access*, vol. 5, pp. 13 868–13 882, 2017.
  38. M. A. Vasarhelyi and H. Issa, "Application of anomaly detection techniques to identify fraudulent refunds," 2011.
  39. Y. Yao, A. Sharma, L. Golubchik, and R. Govindan, "Online anomaly detection for sensor systems: A simple and efficient approach," *Performance Evaluation*, vol. 67, no. 11, pp. 1059–1075, 2010.
  40. M. Amer and S. Abdennadher, "Comparison of unsupervised anomaly detection techniques," Ph.D. dissertation, Bachelors Thesis 2011, [http://www.madm.eu/\\_media/theses/thesis-amer.pdf](http://www.madm.eu/_media/theses/thesis-amer.pdf), 2011.
  41. Z. Ataser and F. N. Alpaslan, "Self-adaptive negative selection using local outlier factor," in *Computer and Information Sciences III*. Springer, 2013, pp. 161–169.
  42. A. K. Abbas, A. H. Lichtman, and S. Pillai, *Cellular and molecular immunology*. Elsevier Health Sciences, 2014.
  43. A. Iwasaki and R. Medzhitov, "Control of adaptive immunity by the innate immune system," *Nature immunology*, vol. 16, no. 4, pp. 343–353, 2015.
  44. S. A. Mohamed Elsayed, R. A. Ammar, and S. Rajasekaran, "Artificial immune systems: Models, applications, and challenges," in *Proceedings of the 27th Annual ACM Symposium on Applied Computing*. ACM, 2012, pp. 256–258.
  45. C.-M. Ou, "Multiagent-based computer virus detection systems: abstraction from dendritic cell algorithm with danger theory," *Telecommunication Systems*, vol. 52, no. 2, pp. 681–691, 2013.
  46. J. V. Kringelum, M. Nielsen, S. B. Padkjær, and O. Lund, "Structural analysis of b-cell epitopes in antibody: protein complexes," *Molecular immunology*, vol. 53, no. 1, pp. 24–34, 2013.

47. C. Haymaker, G. C. Sim, M.-A. Forget, J. Q. Chen, C. Bernatchez, and L. Radvanyi, "The role of the immune system and immunoregulatory mechanisms relevant to melanoma," in *Genetics of Melanoma*. Springer, 2016, pp. 31–65.
48. J. Al-Enezi, "Artificial immune systems based committee machine for classification application," Ph.D. dissertation, Citeseer, 2012.
49. L. N. De Castro and F. J. Von Zuben, "Artificial immune systems: Part i—basic theory and applications," *Technical Report - RT DCA 01/99, School of Computing and Electrical Engineering. State University of Campinas, Brazil*, 1999.
50. S. Darmoul, H. Pierreval, and S. Hajri-Gabouj, "Handling disruptions in manufacturing systems: An immune perspective," *Engineering Applications of Artificial Intelligence*, vol. 26, no. 1, pp. 110–121, 2013.
51. N. F. Mohd Azmi, "Artificial immune systems for information filtering: focusing on profile adaptation," Ph.D. dissertation, University of York, 2014.
52. I. Sela-Culang, V. Kunik, and Y. Ofra, "The structural basis of antibody-antigen recognition," *Frontiers in immunology*, vol. 4, 2013.
53. S. A. Hofmeyr and S. Forrest, "An immunological model of distributed detection and its application to computer security," Ph.D. dissertation, Citeseer, 1999.
54. T. S. Chun, M. Malek, and A. R. Ismail, "A review of wastewater treatment plant modelling: Revolution on modelling technology," *American Journal of Environmental and Resource Economics*, vol. 2, no. 1, pp. 22–26, 2017.
55. M.-G. Masciotta, A. Barontini, L. F. Ramos, P. Amado-Mendes, and P. B. Lourenço, "A bio-inspired framework for highly efficient structural health monitoring and vibration analysis," in *International Conference on Experimental Vibration Analysis for Civil Engineering Structures*. Springer, 2017, pp. 455–468.
56. V. Stantchev, L. Prieto-González, and G. Tamm, "Cloud computing service

- for knowledge assessment and studies recommendation in crowdsourcing and collaborative learning environments based on social network analysis,” *Computers in Human Behavior*, vol. 51, pp. 762–770, 2015.
57. L. N. de Castro and J. Timmis, *Artificial immune systems: a new computational intelligence approach*. Springer Science & Business Media, 2002.
  58. D. Dasgupta, “An overview of artificial immune systems,” In *Dasgupta, D (Ed.), Artificial Immune Systems and Their Applications*, pp. 3–19, 1998.
  59. J. Timmis, “Artificial immune systems: a novel data analysis technique inspired by the immune network theory,” Ph.D. dissertation, Department of Computer Science, 2000.
  60. M. Read, P. S. Andrews, and J. Timmis, “An introduction to artificial immune systems,” in *Handbook of Natural Computing*. Springer, 2012, pp. 1575–1597.
  61. N. K. Jerne, “Towards the network theory of the immune system,” *Ann. Immunol.(Inst. Pasteur)*, vol. 125C, pp. 373–389, 1974.
  62. J. D. Farmer, N. H. Packard, and A. S. Perelson, “The immune system, adaptation, and machine learning,” *Physica D: Nonlinear Phenomena*, vol. 22, no. 1, pp. 187–204, 1986.
  63. Y. Ishida, “Fully distributed diagnosis by pdp learning algorithm: towards immune network pdp model,” in *Neural Networks, 1990., 1990 IJCNN International Joint Conference on*. IEEE, 1990, pp. 777–782.
  64. H. Bersini and F. J. Varela, “Hints for adaptive problem solving gleaned from immune networks,” in *Parallel problem solving from nature*. Springer, 1991, pp. 343–354.
  65. H. Bersini and F. Varela, “The immune learning mechanisms: reinforcement, recruitment and their applications,” *Computing with Biological Metaphors*, vol. 1, no. 2, pp. 166–192, 1994.
  66. L. N. De Castro and F. J. Von Zuben, “The clonal selection algorithm with



- engineering applications,” in *Proceedings of GECCO*, vol. 2000, 2000, pp. 36–39.
67. J. Timmis, M. Neal, and J. Hunt, “An artificial immune system for data analysis,” *Biosystems*, vol. 55, no. 1, pp. 143–150, 2000.
  68. U. Aickelin and S. Cayzer, “The danger theory and its application to artificial immunen systems,” in *Proceedings of the 1st International Conference on ARTificial Immune Systems (ICARIS 2002)*, Canterbury, UK, Sep 9-11 2002, pp. 141–148. [Online]. Available: [http://www.cs.nott.ac.uk/~uxa/papers/icaris\\_danger.pdf](http://www.cs.nott.ac.uk/~uxa/papers/icaris_danger.pdf)
  69. J. Greensmith, U. Aickelin, and S. Cayzer, “Introducing dendritic cells as a novel immune-inspired algorithm for anomaly detection,” in *Artificial Immune Systems*. Springer, 2005, pp. 153–167.
  70. P. Matzinger, “Essay 1: the danger model in its historical context,” *Scandinavian journal of immunology*, vol. 54, no. 1-2, pp. 4–9, 2001.
  71. P. Matzinger, “The danger model: a renewed sense of self,” *Science*, vol. 296, no. 5566, pp. 301–305, 2002.
  72. S. F. M. Burnet *et al.*, *The clonal selection theory of acquired immunity*. Vanderbilt University Press Nashville, 1959, vol. 3.
  73. R. M. Steinman and Z. A. Cohn, “Identification of a novel cell type in peripheral lymphoid organs of mice i. morphology, quantitation, tissue distribution,” *The Journal of experimental medicine*, vol. 137, no. 5, pp. 1142–1162, 1973.
  74. L. E. Jim and M. A. Gregory, “A review of artificial immune system based security frameworks for manet,” *International Journal of Communications, Network and System Sciences*, vol. 9, no. 01, p. 1, 2016.
  75. Z. Chelly and Z. Elouedi, “A survey of the dendritic cell algorithm,” *Knowledge and Information Systems*, vol. 48, no. 3, pp. 505–535, 2016.
  76. Z.-J. Lu, Q. Xiang, and L. Xu, “An application case study on multi-sensor data fusion system for intelligent process monitoring,” *Procedia CIRP*,



- vol. 17, pp. 721–725, 2014.
77. Z. Ji and D. Dasgupta, “V-detector: An efficient negative selection algorithm with probably adequate detector coverage,” *Information sciences*, vol. 179, no. 10, pp. 1390–1406, 2009.
  78. T. Stibor, J. Timmis, and C. Eckert, “A comparative study of real-valued negative selection to statistical anomaly detection techniques,” in *International Conference on Artificial Immune Systems*. Springer, 2005, pp. 262–275.
  79. Z. Ji and D. Dasgupta, “Revisiting negative selection algorithms,” *Evolutionary Computation*, vol. 15, no. 2, pp. 223–251, 2007.
  80. J. K. Percus, O. E. Percus, and A. S. Perelson, “Predicting the size of the t-cell receptor and antibody combining region from consideration of efficient self-nonsel self discrimination,” *Proceedings of the National Academy of Sciences*, vol. 90, no. 5, pp. 1691–1695, 1993.
  81. J. Balthrop, F. Esponda, S. Forrest, and M. Glickman, “Coverage and generalization in an artificial immune system,” in *Proceedings of the Genetic and Evolutionary Computation Conference*. Citeseer, 2002, pp. 3–10.
  82. P. K. Harmer, P. D. Williams, G. H. Gunsch, and G. B. Lamont, “An artificial immune system architecture for computer security applications,” *Evolutionary computation, IEEE transactions on*, vol. 6, no. 3, pp. 252–280, 2002.
  83. J. Chen, D. Yang, and M. Naofumi, “A study of detector generation algorithms based on artificial immune in intrusion detection system,” *WSEAS TRANSACTIONS on BIOLOGY and BIOMEDICINE*, vol. 4, no. 3, pp. 29–35, 2007.
  84. A. Chmielewski and S. T. Wierchoń, “Hybrid negative selection approach for anomaly detection,” in *IFIP International Conference on Computer Information Systems and Industrial Management*. Springer, 2012, pp. 242–253.

85. A. S. Shirkhorshidi, S. Aghabozorgi, and T. Y. Wah, "A comparison study on similarity and dissimilarity measures in clustering continuous data," *PloS one*, vol. 10, no. 12, p. e0144059, 2015.
86. G. C. Silva and D. Dasgupta, "A survey of recent works in artificial immune systems," in *HANDBOOK ON COMPUTATIONAL INTELLIGENCE: Volume 2: Evolutionary Computation, Hybrid Systems, and Applications*. World Scientific, 2016, pp. 547–586.
87. S. N. S. Fakhari and M. T. Ziabari, "A self adaptive algorithm for classification based on negative selection technique," *Artificial Intelligence*, vol. 1, no. 2, 2014.
88. E. Alizadeh, N. Meskin, and K. Khorasani, "A negative selection immune system inspired methodology for fault diagnosis of wind turbines," *IEEE transactions on cybernetics*, 2017.
89. J. Zeng, "Computer malicious executables detection based on real-valued negative selection algorithm," *Applied Mathematics & Information Sciences*, vol. 9, no. 2, p. 1089, 2015.
90. R. Rizwan, F. A. Khan, H. Abbas, and S. H. Chauhdary, "Anomaly detection in wireless sensor networks using immune-based bioinspired mechanism," *International journal of distributed sensor networks*, vol. 11, no. 10, p. 684952, 2015.
91. B. Schmidt and A. Al-Fuqaha, "A new approach to optimized negative selection," in *Evolutionary Computation (CEC), 2016 IEEE Congress on*. IEEE, 2016, pp. 1793–1799.
92. S. M. Mohi-Aldeen, R. Mohamad, and S. Deris, "Application of negative selection algorithm (nsa) for test data generation of path testing," *Applied Soft Computing*, vol. 49, pp. 1118–1128, 2016.
93. S. M. Mohi-Aldeen, R. Mohamad, and S. Deris, "Automated path testing using the negative selection algorithm," *International Journal of Computational Vision and Robotics*, vol. 7, no. 1-2, pp. 160–171, 2017.

94. O. Igbe, O. Ajayi, and T. Saadawi, "Detecting denial of service attacks using a combination of dendritic cell algorithm and the negative selection algorithm," in *Smart Cloud (SmartCloud), 2017 IEEE International Conference on*. IEEE, 2017, pp. 72–77.
95. M. Poggiolini and A. Engelbrecht, "Application of the feature-detection rule to the negative selection algorithm," *Expert Systems with Applications*, vol. 40, no. 8, pp. 3001–3014, 2013.
96. J. Chen, Q. Zhang, and Z. Fang, "Improve the adaptive capability of tma-or," in *Distributed Computing and Artificial Intelligence*. Springer, 2012, pp. 665–671.
97. L.-F. Chen, "An improved negative selection approach for anomaly detection: with applications in medical diagnosis and quality inspection," *Neural Computing and Applications*, vol. 22, no. 5, pp. 901–910, 2013.
98. P. K. Mahapatra, M. Kaur, S. Sethi, R. Thareja, A. Kumar, and S. Devi, "Improved thresholding based on negative selection algorithm (nsa)," *Evolutionary Intelligence*, vol. 6, no. 3, pp. 157–170, 2014.
99. J. Zeng, Z. Qin, and W. Tang, "Anomaly detection using a novel negative selection algorithm," *Journal of Computational and Theoretical Nanoscience*, vol. 10, no. 12, pp. 2831–2835, 2013.
100. G. Chen, L. Zhang, and J. Bao, "An improved negative selection algorithm and its application in the fault diagnosis of vibrating screen by wireless sensor networks," *Journal of Computational and Theoretical Nanoscience*, vol. 10, no. 10, pp. 2418–2426, 2013.
101. R. Zhang, T. Li, and X. Xiao, "A real-valued negative selection algorithm based on grid for anomaly detection," in *Abstract and Applied Analysis*, vol. 2013. Hindawi Publishing Corporation, 2013.
102. S. Chen, "Optimized multilevel immune learning algorithm in abnormal detection," *Information Technology Journal*, vol. 12, no. 3, p. 514, 2013.
103. F. Esponda, S. Forrest, and P. Helman, "A formal framework for positive

- and negative detection schemes,” *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 34, no. 1, pp. 357–373, 2004.
104. D. Zhao and W. Luo, “Real-valued negative databases,” in *Proceedings of the 12th European Conference on Artificial Life (ECAL 2013)*, 2013, pp. 884–890.
  105. Y. Bao, W. Luo, and X. Zhang, “Estimating positive surveys from negative surveys,” *Statistics & Probability Letters*, vol. 83, no. 2, pp. 551–558, 2013.
  106. M. M. Groat, B. Edwards, J. Horey, W. He, and S. Forrest, “Application and analysis of multidimensional negative surveys in participatory sensing applications,” *Pervasive and Mobile Computing*, vol. 9, no. 3, pp. 372–391, 2013.
  107. X. Zheng, Y. Zhou, and Y. Fang, “The dual negative selection algorithm based on pattern recognition receptor theory and its application in two-class data classification,” *Journal of computers*, vol. 8, no. 8, pp. 1951–1959, 2013.
  108. M. Gong, J. Zhang, J. Ma, and L. Jiao, “An efficient negative selection algorithm with further training for anomaly detection,” *Knowledge-Based Systems*, vol. 30, pp. 185–191, 2012.
  109. G. C. Silva, R. M. Palhares, and W. M. Caminhas, “Immune inspired fault detection and diagnosis: A fuzzy-based approach of the negative selection algorithm and participatory clustering,” *Expert Systems with Applications*, vol. 39, no. 16, pp. 12 474–12 486, 2012.
  110. C. Ramdane and S. Chikhi, “A new negative selection algorithm for adaptive network intrusion detection system,” *International Journal of Information Security and Privacy (IJISP)*, vol. 8, no. 4, pp. 1–25, 2014.
  111. J. Zhang and W. Luo, “Evoseedrnasai: An improved evolutionary algorithm for generating detectors in the real-valued negative selection algorithms,” *Applied Soft Computing*, vol. 19, pp. 18–30, 2014.
  112. V. Lytvynenko, “Hybrid swarm negative selection algorithm for dna-microarray data classification,” vol. 800, pp. 134–148, 2014.

113. X. Z. Gao, X. Wang, and K. Zenger, "Motor fault diagnosis using negative selection algorithm," *Neural Computing and Applications*, vol. 25, no. 1, pp. 55–65, 2014.
114. X. Z. Gao, S. J. Ovaska, X. Wang, and M.-Y. Chow, "Multi-level optimization of negative selection algorithm detectors with application in motor fault detection," *Intelligent Automation & Soft Computing*, vol. 16, no. 3, pp. 353–375, 2013.
115. W. Chen, T. Li, X. Liu, and B. Zhang, "A negative selection algorithm based on hierarchical clustering of self set," *Science China Information Sciences*, vol. 56, no. 8, pp. 1–13, 2013.
116. V. Lytvynenko, A. Smolarz, W. Wójcik, J. Ballester, O. Kozhukhovskaya, and K. Gromaszek, "Optical combustion sensor data interpretation using hybrid negative selection algorithm with artificial immune networks," *Mathematical modeling and computing*, vol. 2, no. 1, pp. 58–70, 2015.
117. I. Idris and A. Selamat, "Improved email spam detection model with negative selection algorithm and particle swarm optimization," *Applied Soft Computing*, vol. 22, pp. 11–27, 2014.
118. R. Chikh and S. Chikhi, "Clustered negative selection algorithm and fruit fly optimization for email spam detection," *Journal of Ambient Intelligence and Humanized Computing*, pp. 1–10, 2017.
119. Y. Tan, "Negative selection algorithm with penalty factor," *Artificial Immune System Applications in Computer Security*, pp. 86–100, 2016.
120. J. Zeng and W. Tang, "Negative selection algorithm based unknown malware detection model," in *Bio-Inspired Computing-Theories and Applications*. Springer, 2015, pp. 598–608.
121. F. P. Lima, M. L. Lopes, A. D. P. Lotufo, and C. R. Minussi, "An artificial immune system with continuous-learning for voltage disturbance diagnosis in electrical distribution systems," *Expert Systems with Applications*, vol. 56, pp. 131–142, 2016.

122. S. Fouladvand, A. Osareh, and B. Shadgar, "Distribution estimation based negative selection algorithm (densa)," in *Artificial Immune Systems (AIS), 2015 International Workshop on*. IEEE, 2015, pp. 1–7.
123. S. Fouladvand, A. Osareh, B. Shadgar, M. Pavone, and S. Sharafi, "Densa: An effective negative selection algorithm with flexible boundaries for self-space and dynamic number of detectors," *Engineering Applications of Artificial Intelligence*, vol. 62, pp. 359–372, 2017.
124. A. Abid, M. T. Khan, and C. W. de Silva, "Layered and real-valued negative selection algorithm for fault detection," *IEEE Systems Journal*, pp. 1–10, 2017.
125. T. Wen, A. Xu, and J. Tang, "Study on extension negative selection algorithm," *International Journal of High Performance Computing and Networking*, vol. 9, no. 1-2, pp. 1–7, 2016.
126. T. Yang, W. Chen, and T. Li, "A real negative selection algorithm with evolutionary preference for anomaly detection," *Open Physics*, vol. 15, no. 1, pp. 121–134, 2017.
127. F. Zhu, W. Chen, H. Yang, T. Li, T. Yang, and F. Zhang, "A quick negative selection algorithm for one-class classification in big data era," *Mathematical Problems in Engineering*, vol. 2017, 2017.
128. X. Xiao, T. Li, and R. Zhang, "An immune optimization based real-valued negative selection algorithm," *Applied Intelligence*, vol. 42, no. 2, pp. 289–302, 2015.
129. L. Dong, L. Shulin, and H. Zhang, "A method of anomaly detection and fault diagnosis with online adaptive learning under small training samples," *Pattern Recognition*, vol. 64, pp. 374–385, 2017.
130. X.-S. Yang, S. Deb, M. Loomes, and M. Karamanoglu, "A framework for self-tuning optimization algorithm," *Neural Computing and Applications*, vol. 23, no. 7-8, pp. 2051–2057, 2013.
131. X.-S. Yang, *Nature-inspired optimization algorithms*. Elsevier, 2014.



132. X.-S. Yang, "Swarm intelligence based algorithms: a critical analysis," *Evolutionary intelligence*, vol. 7, no. 1, pp. 17–28, 2014.
133. X. S. Yang and S. Deb, "Cuckoo search: recent advances and applications," *Neural Computing and Applications*, vol. 24, no. 1, pp. 169–174, 2014.
134. A. H. Gandomi, X.-S. Yang, and A. H. Alavi, "Cuckoo search algorithm: a metaheuristic approach to solve structural optimization problems," *Engineering with Computers*, vol. 29, no. 1, pp. 17–35, 2013.
135. A. H. Gandomi, X.-S. Yang, S. Talatahari, and S. Deb, "Coupled eagle strategy and differential evolution for unconstrained and constrained global optimization," *Computers & Mathematics with Applications*, vol. 63, no. 1, pp. 191–200, 2012.
136. D. Wang, D. Tan, and L. Liu, "Particle swarm optimization algorithm: an overview," *Soft Computing*, pp. 1–22, 2017.
137. X.-S. Yang and X. He, "Bat algorithm: literature review and applications," *International Journal of Bio-Inspired Computation*, vol. 5, no. 3, pp. 141–149, 2013.
138. D. Karaboga, B. Gorkemli, C. Ozturk, and N. Karaboga, "A comprehensive survey: artificial bee colony (abc) algorithm and applications," *Artificial Intelligence Review*, vol. 42, no. 1, pp. 21–57, 2014.
139. Y. Kodratoff and R. S. Michalski, *Machine learning: an artificial intelligence approach*. Morgan Kaufmann, 2014, vol. 3.
140. X. Z. Gao, V. Govindasamy, H. Xu, X. Wang, and K. Zenger, "Harmony search method: theory and applications," *Computational intelligence and neuroscience*, vol. 2015, p. 39, 2015.
141. N. S. Jaddi, S. Abdullah, and M. A. Malek, "Master-leader-slave cuckoo search with parameter control for ann optimization and its real-world application to water quality prediction," *PloS one*, vol. 12, no. 1, p. e0170372, 2017.

142. X.-S. Yang, S. Deb, T. Hanne, and X. He, "Attraction and diffusion in nature-inspired optimization algorithms," *Neural Computing and Applications*, pp. 1–8, 2015.
143. S. Sanajaoba and E. Fernandez, "Maiden application of cuckoo search algorithm for optimal sizing of a remote hybrid renewable energy system," *Renewable Energy*, vol. 96, pp. 1–10, 2016.
144. S. A. Elazim and E. Ali, "Optimal power system stabilizers design via cuckoo search algorithm," *International Journal of Electrical Power & Energy Systems*, vol. 75, pp. 99–107, 2016.
145. W. Lim, G. Kanagaraj, and S. Ponnambalam, "A hybrid cuckoo search-genetic algorithm for hole-making sequence optimization," *Journal of Intelligent Manufacturing*, vol. 27, no. 2, pp. 417–429, 2016.
146. M. S. Rao and N. Venkaiah, "A modified cuckoo search algorithm to optimize wire-edm process while machining inconel-690," *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, vol. 39, no. 5, pp. 1647–1661, 2017.
147. X. Zhang, J. Wang, and K. Zhang, "Short-term electric load forecasting based on singular spectrum analysis and support vector machine optimized by cuckoo search algorithm," *Electric Power Systems Research*, vol. 146, pp. 270–285, 2017.
148. Z. Cui, B. Sun, G. Wang, Y. Xue, and J. Chen, "A novel oriented cuckoo search algorithm to improve dv-hop performance for cyber-physical systems," *Journal of Parallel and Distributed Computing*, vol. 103, pp. 42–52, 2017.
149. N. Fouladgar, M. Hasanipanah, and H. B. Amnieh, "Application of cuckoo search algorithm to estimate peak particle velocity in mine blasting," *Engineering with Computers*, vol. 33, no. 2, pp. 181–189, 2017.
150. W. Sun and J. Sun, "Daily pm 2.5 concentration prediction based on principal component analysis and lssvm optimized by cuckoo search algorithm,"



- Journal of environmental management*, vol. 188, pp. 144–152, 2017.
151. A. M. Reynolds and M. A. Frye, “Free-flight odor tracking in drosophila is consistent with an optimal intermittent scale-free search,” *PloS one*, vol. 2, no. 4, p. e354, 2007.
  152. A. J. MacIntosh, L. Pelletier, A. Chiaradia, A. Kato, and Y. Ropert-Coudert, “Temporal fractals in seabird foraging behaviour: diving through the scales of time,” *Scientific reports*, vol. 3, 2013.
  153. O. Miramontes, O. DeSouza, L. R. Paiva, A. Marins, and S. Orozco, “Lévy flights and self-similar exploratory behaviour of termite workers: beyond model fitting,” *PloS one*, vol. 9, no. 10, p. e111183, 2014.
  154. P. López-López, J. Benavent-Corai, C. García-Ripollés, and V. Urios, “Scavengers on the move: behavioural changes in foraging search patterns during the annual cycle,” *PLoS One*, vol. 8, no. 1, p. e54352, 2013.
  155. Y. Ling, Y. Zhou, and Q. Luo, “Lévy flight trajectory-based whale optimization algorithm for global optimization,” *IEEE Access*, vol. 5, pp. 6168–6186, 2017.
  156. Z. Li, Y. Zhou, S. Zhang, and J. Song, “Lévy-flight moth-flame algorithm for function optimization and engineering design problems,” *Mathematical Problems in Engineering*, vol. 2016, 2016.
  157. P. Saxena and A. Kothari, “Linear antenna array optimization using flower pollination algorithm,” *SpringerPlus*, vol. 5, no. 1, p. 306, 2016.
  158. H. Ghafarzadeh and A. Bouyer, “An efficient hybrid clustering method using an artificial bee colony algorithm and mantegna lévy distribution,” *International Journal on Artificial Intelligence Tools*, vol. 25, no. 02, p. 1550034, 2016.
  159. X.-S. Yang and S. Deb, “Engineering optimisation by cuckoo search,” *International Journal of Mathematical Modelling and Numerical Optimisation*, vol. 1, no. 4, pp. 330–343, 2010.
  160. X.-S. Yang, “Cuckoo search and firefly algorithm: overview and analysis,” in

- Cuckoo Search and Firefly Algorithm*. Springer, 2014, pp. 1–26.
161. F. Wang, X.-S. He, Y. Wang, and S.-M. Yang, “Markov model and convergence analysis based on cuckoo search algorithm,” *Jisuanji Gongcheng/ Computer Engineering*, vol. 38, no. 11, 2012.
  162. H. Rakhshani, E. Dehghanian, and A. Rahati, “Hierarchy cuckoo search algorithm for parameter estimation in biological systems,” *Chemometrics and Intelligent Laboratory Systems*, vol. 159, pp. 97–107, 2016.
  163. L. Wang, Y. Zhong, and Y. Yin, “A hybrid cooperative cuckoo search algorithm with particle swarm optimisation,” *International Journal of Computing Science and Mathematics*, vol. 6, no. 1, pp. 18–29, 2015.
  164. P. Civicioglu and E. Besdok, “A conceptual comparison of the cuckoo-search, particle swarm optimization, differential evolution and artificial bee colony algorithms,” *Artificial Intelligence Review*, vol. 39, no. 4, pp. 315–346, 2013.
  165. Q. Liao, S. Zhou, H. Shi, and W. Shi, “Parameter estimation of nonlinear systems by dynamic cuckoo search,” *Neural Computation*, vol. 29, no. 4, pp. 1103–1123, 2017.
  166. A. F. Ali and M. A. Tawhid, “A hybrid cuckoo search algorithm with nelder mead method for solving global optimization problems,” *SpringerPlus*, vol. 5, no. 1, p. 473, 2016.
  167. R. Knobloch, J. Mlýnek, and R. Srb, “The classic differential evolution algorithm and its convergence properties,” *Applications of Mathematics*, vol. 62, no. 2, pp. 197–208, 2017.
  168. M. F. Tasgetiren, P. Suganthan, S. Ozcan, and D. Kizilay, “A differential evolution algorithm with a variable neighborhood search for constrained function optimization,” in *Adaptation and hybridization in computational intelligence*. Springer, 2015, pp. 171–184.
  169. K. Y. Kok and P. Rajendran, “Differential-evolution control parameter optimization for unmanned aerial vehicle path planning,” *PloS one*, vol. 11, no. 3, p. e0150558, 2016.

170. A. W. Mohamed and A. S. Almazyad, "Differential evolution with novel mutation and adaptive crossover strategies for solving large scale global optimization problems," *Applied Computational Intelligence and Soft Computing*, vol. 2017, 2017.
171. M. Salehpour, A. Jamali, A. Bagheri, and N. Nariman-zadeh, "A new adaptive differential evolution optimization algorithm based on fuzzy inference system," *Engineering Science and Technology, an International Journal*, vol. 20, no. 2, pp. 587–597, 2017.
172. L. Zhang, L. Liu, X.-S. Yang, and Y. Dai, "A novel hybrid firefly algorithm for global optimization," *PloS one*, vol. 11, no. 9, p. e0163230, 2016.
173. X. Zhao, W. Lin, C. Yu, J. Chen, and S. Wang, "A new hybrid differential evolution with simulated annealing and self-adaptive immune operation," *Computers & Mathematics with Applications*, vol. 66, no. 10, pp. 1948–1960, 2013.
174. S. Das, S. S. Mullick, and P. N. Suganthan, "Recent advances in differential evolution—an updated survey," *Swarm and Evolutionary Computation*, vol. 27, pp. 1–30, 2016.
175. X.-S. Yang and S. Deb, "Two-stage eagle strategy with differential evolution," *International Journal of Bio-Inspired Computation*, vol. 4, no. 1, pp. 1–5, 2012.
176. V. Shemyakin *et al.*, "Differential evolution approach and parameter estimation of chaotic," 2012.
177. Z. Liu, Y. Wang, S. Yang, and Z. Cai, "Tsde: A new differential evolution with two-stage optimization strategies for numerical optimization." IEEE Press, 2016.
178. V. Vapnik, *The nature of statistical learning theory*. Springer Science & Business Media, 2013.
179. V. Vapnik and R. Izmailov, "Learning using privileged information: similarity control and knowledge transfer." *Journal of machine learning*

- research*, vol. 16, no. 20232049, p. 55, 2015.
180. R. de Pádua Moreira and C. L. Nascimento, "Prognostics of aircraft bleed valves using a svm classification algorithm," in *Aerospace Conference, 2012 IEEE*. IEEE, 2012, pp. 1–8.
  181. Q. Kang, L. Shi, M. Zhou, X. Wang, Q. Wu, and Z. Wei, "A distance-based weighted undersampling scheme for support vector machines and its application to imbalanced classification," *IEEE Transactions on Neural Networks and Learning Systems*, pp. 1–14, 2017.
  182. B. Gu, V. S. Sheng, K. Y. Tay, W. Romano, and S. Li, "Incremental support vector learning for ordinal regression," *IEEE Transactions on Neural networks and learning systems*, vol. 26, no. 7, pp. 1403–1416, 2015.
  183. L. J. Cao, S. S. Keerthi, C. J. Ong, J. Zhang, U. Periyathamby, X. J. Fu, and H. Lee, "Parallel sequential minimal optimization for the training of support vector machines," *IEEE Transactions on Neural Networks*, vol. 17, no. 4, pp. 1039–1049, 2006.
  184. D.-M. Filimon and A. Albu, "Skin diseases diagnosis using artificial neural networks." in *SACI*, 2014, pp. 189–194.
  185. H. Li, D. Yang, F. Chen, Y. Zhou, and Z. Xiu, "Application of artificial neural networks in predicting abrasion resistance of solution polymerized styrene-butadiene rubber based composites," in *Electronics, Computer and Applications, 2014 IEEE Workshop on*. IEEE, 2014, pp. 581–584.
  186. Q.-s. Li, D.-z. Li, and L.-l. Cao, "Modeling and optimum operating conditions for fccu using artificial neural network," *Journal of Central South University*, vol. 22, no. 4, pp. 1342–1349, 2015.
  187. Z. Dan, "Improving the accuracy in software effort estimation: Using artificial neural network model based on particle swarm optimization," in *Service Operations and Logistics, and Informatics (SOLI), 2013 IEEE International Conference on*. IEEE, 2013, pp. 180–185.
  188. Z. Zhang, "Artificial neural network," in *Multivariate Time Series Analysis in*

- Climate and Environmental Research*. Springer, 2018, pp. 1–35.
189. M. Muja and D. G. Lowe, “Scalable nearest neighbor algorithms for high dimensional data,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 36, no. 11, pp. 2227–2240, 2014.
  190. D. Adeniyi, Z. Wei, and Y. Yongquan, “Automated web usage data mining and recommendation system using k-nearest neighbor (knn) classification method,” *Applied Computing and Informatics*, vol. 12, no. 1, pp. 90–108, 2016.
  191. I. Saini, D. Singh, and A. Khosla, “Qrs detection using k-nearest neighbor algorithm (knn) and evaluation on standard ecg databases,” *Journal of advanced research*, vol. 4, no. 4, pp. 331–344, 2013.
  192. H. Sahin and A. Subasi, “Classification of the cardiotocogram data for anticipation of fetal risks using machine learning techniques,” *Applied Soft Computing*, vol. 33, pp. 231–238, 2015.
  193. D. T. Larose, *Discovering knowledge in data: an introduction to data mining*. John Wiley & Sons, 2014.
  194. P. Bermejo, J. A. Gámez, and J. M. Puerta, “Speeding up incremental wrapper feature subset selection with naive bayes classifier,” *Knowledge-Based Systems*, vol. 55, pp. 140–147, 2014.
  195. D. M. Farid, L. Zhang, C. M. Rahman, M. A. Hossain, and R. Strachan, “Hybrid decision tree and naïve bayes classifiers for multi-class classification tasks,” *Expert Systems with Applications*, vol. 41, no. 4, pp. 1937–1946, 2014.
  196. S. Mukherjee and N. Sharma, “Intrusion detection using naive bayes classifier with feature reduction,” *Procedia Technology*, vol. 4, pp. 119–128, 2012.
  197. A. Dangi and S. Srivastava, “Educational data classification using selective naive bayes for quota categorization,” in *MOOC, Innovation and Technology in Education (MITE), 2014 IEEE International Conference on*. IEEE, 2014, pp. 118–121.

198. S. Agrawal and J. Agrawal, "Survey on anomaly detection using data mining techniques," *Procedia Computer Science*, vol. 60, pp. 708–713, 2015.
199. M. H. Bhuyan, D. K. Bhattacharyya, and J. K. Kalita, "Network anomaly detection: methods, systems and tools," *IEEE Communications Surveys & Tutorials*, vol. 16, no. 1, pp. 303–336, 2014.
200. F. Provost and T. Fawcett, *Data Science for Business: What you need to know about data mining and data-analytic thinking*. " O'Reilly Media, Inc.", 2013.
201. A. A. Freitas, *Data mining and knowledge discovery with evolutionary algorithms*. Springer Science & Business Media, 2013.
202. M. Bengtsson, "How to plan and perform a qualitative study using content analysis," *NursingPlus Open*, vol. 2, pp. 8–14, 2016.
203. E. Begoli and J. Horey, "Design principles for effective knowledge discovery from big data," in *Software Architecture (WICSA) and European Conference on Software Architecture (ECSA), 2012 joint working IEEE/IFIP conference on*. IEEE, 2012, pp. 215–218.
204. K. Bache and M. Lichman, "UCI machine learning repository," 2013. [Online]. Available: <http://archive.ics.uci.edu/ml>
205. R. A. Fisher, "The use of multiple measurements in taxonomic problems," *Annals of eugenics*, vol. 7, no. 2, pp. 179–188, 1936.
206. W. H. Wolberg and O. L. Mangasarian, "Multisurface method of pattern separation for medical diagnosis applied to breast cytology." *Proceedings of the national academy of sciences*, vol. 87, no. 23, pp. 9193–9196, 1990.
207. R. Forsyth, "Pc/beagle user's guide," *BUPA Medical Research Ltd*, 1990.
208. J. Cendrowska, "Prism: An algorithm for inducing modular rules," *International Journal of Man-Machine Studies*, vol. 27, no. 4, pp. 349–370, 1987.
209. J. W. Smith, J. Everhart, W. Dickson, W. Knowler, and R. Johannes, "Using the adap learning algorithm to forecast the onset of diabetes mellitus," in



- Proceedings of the Annual Symposium on Computer Application in Medical Care.* American Medical Informatics Association, 1988, p. 261.
210. R. S. Siegler, "Three aspects of cognitive development," *Cognitive psychology*, vol. 8, no. 4, pp. 481–520, 1976.
  211. S. B. Thrun, J. Bala, E. Bloedorn, I. Bratko, B. Cestnik, J. Cheng, K. D. Jong, S. Dzeroski, S. E. Fahlman, D. Fisher, R. Hamann, K. Kaufman, S. Keller, I. Kononenko, J. Kreuziger, R. Michalski, T. Mitchell, P. Pachowicz, Y. Reich, H. Vafaie, W. V. D. Welde, W. Wenzel, J. Wnek, and J. Zhang, "The monk's problems: A performance comparison of different learning algorithms," Technical Report CS-CMU-91-197, Carnegie Mellon University, Tech. Rep., 1991.
  212. J. Wnek, J. Sarma, A. A. Wahab, and R. S. Michalski, "Comparing learning paradigms via diagrammatic visualization: A case study in single concept learning using symbolic, neural net and genetic algorithm methods," *Methodologies for intelligent systems*, vol. 5, pp. 428–437, 1990.
  213. R. B. Bhatt, G. Sharma, A. Dhall, and S. Chaudhury, "Efficient skin region segmentation using low complexity fuzzy decision tree model," in *2009 Annual IEEE India Conference*. IEEE, 2009, pp. 1–4.
  214. A. Dhall, G. Sharma, R. Bhatt, and G. M. Khan, "Adaptive digital makeup," in *International Symposium on Visual Computing*. Springer, 2009, pp. 728–736.
  215. V. Lohweg, J. L. Hoffmann, H. Dörksen, R. Hildebrand, E. Gillich, J. Hofmann, and J. Schaede, "Banknote authentication with mobile devices," in *IS&T/SPIE Electronic Imaging*. International Society for Optics and Photonics, 2013, pp. 866 507–866 507.
  216. V. Lohweg, R. Li, T. Türke, H. Willeke, and J. Schaede, "Fpga-based multisensor real-time machine vision for banknote printing," 2009.
  217. V. Lohweg, H. Dörksen, E. Gillich, R. Hildebrand, J. Hoffmann, and J. Schaede, "Mobile devices for banknote authentication—is it possible?"

- in *Optical Document Security-The Conference on Optical Security and Counterfeit Detection*, vol. 3, 2012, pp. 1–12.
218. A.-J. Hempel, H. Hähnel, U. Mönks, and V. Lohweg, “Svm-integrated fuzzy pattern classification for nonconvex data-inherent structures applied to banknote authentication,” *Bildverarbeitung in der Automation. inIT, Lemgo*, 2012.
  219. L. Cox, M. Johnson, and K. Kafadar, “Exposition of statistical graphics technology,” *ASA Proceedings of the Statistical Computation Section*, pp. 55–56, 1982.
  220. K. He, L. Yu, and K. K. Lai, “Crude oil price analysis and forecasting using wavelet decomposed ensemble model,” *Energy*, vol. 46, no. 1, pp. 564–574, 2012.
  221. A. Charles and O. Darné, “The efficiency of the crude oil markets: Evidence from variance ratio tests,” *Energy Policy*, vol. 37, no. 11, pp. 4267–4272, 2009.
  222. H. Chiroma and S. Abdulkareem, “Neuro-genetic model for crude oil price prediction while considering the impact of uncertainties,” *International Journal of Oil, Gas and Coal Technology*, vol. 12, no. 3, pp. 302–333, 2016.
  223. M. O. Adetutu, “Energy efficiency and capital-energy substitutability: Evidence from four opec countries,” *Applied Energy*, vol. 119, pp. 363–370, 2014.
  224. M. Panella, F. Barcellona, and R. L. D’ecclesia, “Forecasting energy commodity prices using neural networks,” *Advances in Decision Sciences*, vol. 2012, 2012.
  225. H. Chiroma, S. Abdulkareem, A. Abubakar, and M. J. Usman, “Computational intelligence techniques with application to crude oil price projection: a literature survey from 2001-2012,” *Neural Network World*, vol. 23, no. 6, p. 523, 2013.
  226. S. García, J. Luengo, and F. Herrera, *Data preprocessing in data mining*.



- Springer, 2015.
227. J. Han, M. Kamber, and J. Pei, *Data Mining: Concepts and Techniques*. Morgan Kaufmann, Elsevier, 2011.
  228. M. J. Zaki and W. Meira Jr, *Data mining and analysis: fundamental concepts and algorithms*. Cambridge University Press, New York, NY, USA, 2014.
  229. S. García, J. Luengo, and F. Herrera, "Tutorial on practical tips of the most influential data preprocessing algorithms in data mining," *Knowledge-Based Systems*, vol. 98, pp. 1–29, 2016.
  230. J. Barnard and X.-L. Meng, "Applications of multiple imputation in medical studies: from aids to nhanes," *Statistical methods in medical research*, vol. 8, no. 1, pp. 17–36, 1999.
  231. A. Farhangfar, L. Kurgan, and J. Dy, "Impact of imputation of missing values on classification error for discrete data," *Pattern Recognition*, vol. 41, no. 12, pp. 3692–3705, 2008.
  232. H. Kang, "The prevention and handling of the missing data," *Korean journal of anesthesiology*, vol. 64, no. 5, pp. 402–406, 2013.
  233. M. Saar-Tsechansky and F. Provost, "Handling missing values when applying classification models," *Journal of machine learning research*, vol. 8, no. Jul, pp. 1623–1657, 2007.
  234. F. Cismondi, A. S. Fialho, S. M. Vieira, S. R. Reti, J. M. Sousa, and S. N. Finkelstein, "Missing data in medical databases: Impute, delete or classify?" *Artificial intelligence in medicine*, vol. 58, no. 1, pp. 63–72, 2013.
  235. M. F. M. Mohsin, A. R. Hamdan, and A. A. Bakar, "The effect of normalization for real value negative selection algorithm," in *Soft computing applications and intelligent systems*. Springer, 2013, pp. 194–205.
  236. J. Han and M. Kamber, "Data mining: Concepts and techniques," 2006.
  237. B. Mishra and K. Shukla, "Data mining techniques for software quality prediction," *Software Design and Development: Concepts, Methodologies, Tools, and Applications: Concepts, Methodologies, Tools, and Applications*,

- p. 401, 2013.
238. H. Chiroma, S. Abdul-Kareem, A. Khan, N. M. Nawawi, A. Y. Gital, L. Shuib, A. I. Abubakar, M. Z. Rahman, and T. Herawan, "Global warming: Predicting opec carbon dioxide emissions from petroleum consumption using neural network and hybrid cuckoo search algorithm," *PloS one*, vol. 10, no. 8, p. e0136140, 2015.
  239. H. Chiroma, S. Abdulkareem, and T. Herawan, "Evolutionary neural network model for west texas intermediate crude oil price prediction," *Applied Energy*, vol. 142, pp. 266–273, 2015.
  240. Y.-W. Chang, C.-J. Hsieh, K.-W. Chang, M. Ringgaard, and C.-J. Lin, "Training and testing low-degree polynomial data mappings via linear svm," *Journal of Machine Learning Research*, vol. 11, no. Apr, pp. 1471–1490, 2010.
  241. A. A. Freitas and J. Timmis, "Revisiting the foundations of artificial immune systems: A problem-oriented perspective," in *International Conference on Artificial Immune Systems*. Springer, 2003, pp. 229–241.
  242. Z. Jinquan, L. Xiaojie, L. Tao, L. Caiming, P. Lingxi, and S. Feixian, "A self-adaptive negative selection algorithm used for anomaly detection," *Progress in natural Science*, vol. 19, no. 2, pp. 261–266, 2009.
  243. Z. Ji and D. Dasgupta, "Applicability issues of the real-valued negative selection algorithms," in *Proceedings of the 8th annual conference on Genetic and evolutionary computation*. ACM, 2006, pp. 111–118.
  244. Y. Liang, H. Yang, J. Fu, C. Tan, A. Liu, and S. Zhu, "The effect of real-valued negative selection algorithm on web server aging detection," *Journal of Software*, vol. 7, no. 4, pp. 849–855, 2012.
  245. Z. Ji, *Negative Selection Algorithms: from the Thymus to V-detector*. The University of Memphis, 2006.
  246. L. Cui, D. Pi, and C. Chen, "Biorv-nsa: Bidirectional inhibition optimization r-variable negative selection algorithm and its application," *Applied Soft*

- Computing*, vol. 32, pp. 544–552, 2015.
247. E. Cuevas and A. Reyna-Orta, “A cuckoo search algorithm for multimodal optimization,” *The Scientific World Journal*, vol. 2014, 2014.
  248. E. Cuevas, M. A. D. Cortés, and D. A. O. Navarro, “A states of matter algorithm for global optimization,” in *Advances of Evolutionary Computation: Methods and Operators*. Springer, 2016, pp. 35–54.
  249. M. Rosu, P. Zhou, D. Lin, D. M. Ionel, M. Popescu, F. Blaabjerg, V. Rallabandi, and D. Staton, *Multiphysics Simulation by Design for Electrical Machines, Power Electronics and Drives*. John Wiley & Sons, 2017.
  250. M. Dourado, J. Meireles, and A. M. A. Rocha, “A global optimization approach applied to structural dynamic updating,” in *International Conference on Computational Science and Its Applications*. Springer, 2014, pp. 195–210.
  251. B. Biggio, G. Fumera, I. Pillai, and F. Roli, “A survey and experimental evaluation of image spam filtering techniques,” *Pattern Recognition Letters*, vol. 32, no. 10, pp. 1436–1446, 2011.
  252. M. Friedman, “The use of ranks to avoid the assumption of normality implicit in the analysis of variance,” *Journal of the american statistical association*, vol. 32, no. 200, pp. 675–701, 1937.
  253. M. Friedman, “A comparison of alternative tests of significance for the problem of m rankings,” *The Annals of Mathematical Statistics*, vol. 11, no. 1, pp. 86–92, 1940.
  254. J. Demšar, “Statistical comparisons of classifiers over multiple data sets,” *Journal of Machine learning research*, vol. 7, pp. 1–30, 2006.
  255. S. García, A. Fernández, J. Luengo, and F. Herrera, “Advanced nonparametric tests for multiple comparisons in the design of experiments in computational intelligence and data mining: Experimental analysis of power,” *Information Sciences*, vol. 180, no. 10, pp. 2044–2064, 2010.

256. J. Derrac, S. García, D. Molina, and F. Herrera, “A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms,” *Swarm and Evolutionary Computation*, vol. 1, no. 1, pp. 3–18, 2011.
257. S. Garcia and F. Herrera, “An extension on “statistical comparisons of classifiers over multiple data sets” for all pairwise comparisons,” *Journal of Machine Learning Research*, vol. 9, pp. 2677–2694, 2008.
258. S. Holm, “A simple sequentially rejective multiple test procedure,” *Scandinavian journal of statistics*, vol. 6, pp. 65–70, 1979.
259. D. Li, S. Liu, and H. Zhang, “Negative selection algorithm with constant detectors for anomaly detection,” *Applied Soft Computing*, vol. 36, pp. 618–632, 2015.
260. D. Li, S. Liu, and H. Zhang, “A negative selection algorithm with online adaptive learning under small samples for anomaly detection,” *Neurocomputing*, vol. 149, pp. 515–525, 2015.
261. “Statistical inference in computational intelligence and data mining,” May 16 2017. [Online]. Available: <http://sci2s.ugr.es/sicidm>

